IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received 22 June 2022, accepted 11 July 2022, date of publication 14 July 2022, date of current version 20 July 2022.

Digital Object Identifier 10.1109/ACCESS.2022.3190967

TOPICAL REVIEW

A Systematic Literature Review on Machine Learning Algorithms for Human Status Detection

SUMAN KALYAN SARDAR, NAVEEN KUMAR, AND SEUL CHAN LEE
Department of Industrial and Systems Engineering, Gyeongsang National University, Jinju 52828, South Korea

Corresponding author: Seul Chan Lee (seulchan@gnu.ac.kr)

This work was supported by the Basic Science Research Program through the National Research Foundation of Korea (NRF) funded by the Ministry of Education under Grant 2020R1I1A3067932.

ABSTRACT Human status detection (HSD) is important to understand the status of users when interacting with various systems under different conditions. Recently, although various machine learning algorithms have been applied to analyze and detect human status, there are no guidelines to utilize machine learning algorithms to analyze physical, cognitive, and emotional aspects of human status. Therefore, this study aimed to investigate measures, tools, and machine learning algorithms for HSD by applying a systematic literature review method. We followed the preferred reporting items for systematic reviews and meta-analysis (PRISMA) model to answer three research questions related to the research objective. A total of 76 articles were identified using two hundred keyword combinations addressing topics under HSD in the fields of human factors and human-computer interaction (HCI). The results showed that research on HSD becomes important in industrial systems, focusing on how intelligent systems based on machine learning (ML) differ from earlier generations of automated systems, and what these differences necessarily imply for HCI to design and evaluation. The tools used to collect data for HSD on different parameters are broadly discussed. Recent HSD studies seem to focus on cognitive load and emotion, whereas prior studies have focused on the detection of physical effort. This research assists domain researchers in identifying HSD approaches using different ML algorithms that are suitable for use in their research.

INDEX TERMS Human status detection, physical status, cognitive status, emotional status, machine learning algorithms.

I. INTRODUCTION

Human status detection (HSD) is important in human-computer interaction (HCI) fields to understand users' status. Researchers and practitioners in this field can provide design insights by capturing physical, cognitive, and emotional status. Traditionally, perceived user data from self-reporting methods such as questionnaire have been widely used to observe human status because it is simple, intuitive, and effective. However, these approaches have a weak point that users sometimes do not know themselves exactly [1]. Recently, with the development of data collection and analysis technologies, the HSD using physiological data becomes another major method. As physiological indices on heart, skin, muscle, and eye movements can directly provide information about the human status, researchers and practitioners do not necessarily need to ask users about their status.

There are two aspects enabling this technology to use in HSD: (1) sensing technologies and (2) analysis techniques. Due to the advancement of sensors (e.g., miniaturization and wireless), it is easier to get physiological data than before [2]. Even we can collect the data using a commercial products like wearable devices. The second factor is the advancement of big data analysis on physiological data using machine learning (ML) algorithms [3]. The overall process of analyzing data using ML algorithms in these areas consists of three main phases. In the first phase, data acquisition is performed using different tools. The second phase involves the process of feature extraction from the acquired data. The classification of the extracted features is performed in the third phase to check efficiency. ML approaches are effective for analyzing and forecasting physical, cognitive, and emotional states, as well

The associate editor coordinating the review of this manuscript and approving it for publication was Giuseppe Desolda.

as encouraging autonomy [4]. ML is a technology that allows adaptive automation to reach its full potential. It is extremely useful for analyzing massive datasets of HSD, it also allows the machine to comprehend human behaviors.

Although ML algorithms have been rapidly advancing with the syndrome of artificial intelligence in the world, it is still difficult to utilize in HCI fields. As physiological data from the human body are very sensitive and fluctuated, only unstructured data is available when analyzing the data with ML algorithms [5]. Therefore, without a careful selection of ML algorithms depending on the data type, it is highly likely that the model performance is lower than expected as well as not knowing the decision process.

With this background, in this study, we aimed to provide the holistic understanding of HSD using ML algorithms based on a systematic literature review (SLR) method. We seek to offer a comprehensive review of available research that investigates HSD using ML algorithms in HCI fields. The study structure in terms of domain classification is shown in Fig. 1. Physical, cognitive, and emotion are considered the main components of human status and have been widely investigated in HCI and Human Factors (HF) fields. Physiological data are collected using different data acquisition tools to detect physical, cognitive, and emotional status by analyzing the data. Physiological indices on the heart, skin, muscle, and eye are considered to detect physical state [6]. The cognitive state refers to the part of the brain that deals with reasoning and process such as memory and attention whereas the emotional state refers to emotions [7].

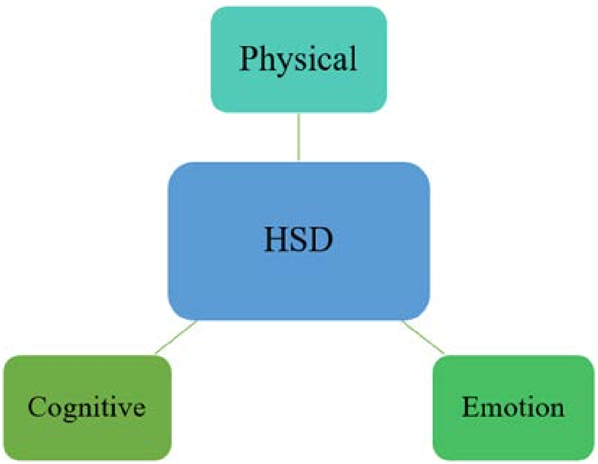

FIGURE 1. HSD domain classification.

The information gathered for the HSD is divided into two categories: quantitative and qualitative. Collected data are analyzed using different ML algorithms to detect human status. Feature selection and classification are performed depending on the data parameters. Based on these components, the following research questions are addressed:

- RQ1: What kind of data are collected for detecting human status in existing research?
- RQ2: How are the data collected using different data acquisition tools for human status detection?
- RQ3: What type of machine learning and deep learning algorithms are applied to analyze the human status data?

This study makes three important contributions: (1) a comprehensive mapping of the current literature on HSD, (2) a discussion of the results based on data acquisition tools, and (3) a feature analysis of ML/DL algorithms with an overview of future research paths. This review is planning to start a cumulative research tradition in the future. The reminder of this paper is organized as follows: Section 2 contains the literature based on previous studies. Section 3 covers the methodology for conducting SLR. The results based on the RQs are presented in Section 4. This section's understanding of HSD in terms of data acquisition for feature analysis and classification using various ML/DL algorithms is abstracted because it is meant to be an in-depth analysis of the area for interested scientists and researchers. Section 5 presents the discussion and future aspects. Finally, concluding remarks are presented in Section 6.

II. LITERATURE REVIEW

Research on HSD began in the late 1970s and HSD has a wide range of applications in the field of HCI [8]. An examination of operators' behaviors, perceptions, and emotions may reveal potential threats when interacting with systems and devices, enabling us to manage these instances more effectively. HCI uses traditional processes to control and communicate when interacting between humans and machines [9]. Improved data acquisition techniques are invented with new devices but most of the methods are still following traditional processes. HSD can be used as an observation tool that uses data on physical, cognitive, emotional, and monitoring capacities [10] while adapting to data quality trade-offs [11]. The use of machine learning (ML) algorithms to analyze data and develop applications has been increasing in many areas, such as intelligent tutoring, robotics, medical diagnosis, stress recognition, and decision support [12].

A literature review is conducted to gain an understanding of the existing research on HSD, considering all important aspects from data acquisition to data processing for identifying human status. The overall process of analyzing data using ML algorithms in these areas consists of three main phases. In the first phase, data acquisition is performed using different tools. The second phase involves the process of feature extraction from the acquired data. The classification of the extracted features is performed in the third phase to check efficiency. Detailed explanations of these three phases are provided below.

A. DATA ACQUISITION

Physiological data used to identify human status is often analog, and it is transformed to digital form for analysis [13]. To acquire the data, different data acquisition tools are used. The data obtained under ideal conditions are devoid of noise and artifacts. There are numerous approaches to understanding human status. Techniques for collecting data include invasive, semi-invasive, and non-invasive approaches. According to this study, methods used to detect human status are electroencephalography (EEG), functional magnetic resonance imaging (fMRI), electrocorticography (ECoG), electrocardiography (ECG), electromyography (EMG), eye-tracking, and magnetic resonance imaging (MRI). The acquisition of appropriate data is the first step in information retrieval [14]. Different data acquisition techniques are described below.

1) ELECTROENCEPHALOGRAPHY (EEG)

EEG is a technique used to determine anomalies in brain electrical activity. The findings appear as wavy lines on the output console. Electrodes, which are connected to the skull with the assistance of adhesive, conducting substances, are used to capture impulses from the brain. It is a simple process that yields trace matching in different brain areas [15]. According to Mousa *et al.* [16], EEG is sensitive to secondary current characteristics. The data acquisition procedure comprises electrodes collecting data from the scalp, amplifiers increasing the data amplitude, an A/D converter digitizing the analog data, and a recording device for storing and displaying the processed data. The 10–20 international system dominates the positioning of electrodes on the scalp.

2) FUNCTIONAL MAGNETIC RESONANCE IMAGING (fMRI)

fMRI is another data collection approach that provides a structural and functional perspective of the brain [17]. fMRI has the advantage of being able to image specific brain regions while the person is performing certain behaviors. With the use of variations in blood flow to specific areas of the brain, it can detect which sections of the brain are engaged during each task. The fact that hemoglobin in human blood is magnetic and hence responds strongly to the magnetic field utilized in fMRI provides substantial temporal evidence. Even with short simulation durations, fMRI may detect activity [18]. The finding of good or incorrect functioning of regions is based on relative variances in the hemoglobin response in diverse regions.

3) ELECTROCORTICOGRAPHY (ECoG)

Invasive data acquisition has health restrictions, stability, and permanence difficulties, which ECoG addresses [19]. The performance of ECoG in two-dimensional tasks was validated by Kang [20] and demonstrated how it outperformed invasive approaches. Furthermore, epidural ECoG (EECoG), a form of ECoG, is superior to standard ECoG. These techniques allow individuals to be rehabilitated with minimal invasiveness and high precision.

4) ELECTROCARDIOGRAPHY (ECG)

ECG is a technique used to measure and record the electrical potentials of the heart [21]. Electrical activities are picked up by ECG acquisition equipment via sensors attached to the human skin, and the electrical activities are drawn in millivolt ranges. During the normal cardiac function, both atria contract together, followed by ventricular contraction [22]. The depolarization and repolarization stages of the muscle fibers of the heart can be roughly separated into ECGs. Basic features (amplitudes and time intervals) are provided by the ECG data analysis and classification system, which are used in the automatic analysis [23]. Several studies have resulted in the development of numerous arrhythmia classification techniques. Digital data analysis, fuzzy logic, genetic algorithms (GA), artificial neural networks (ANN), self-organizing maps, support vector machines, bayesian and wavelet-domain hidden Markov models, and others are among these methodologies. This document provides a broad overview of the various strategies and works that have been proposed.

5) ELECTROMYOGRAPHY (EMG)

EMG data are quickly becoming one of the most important biological characteristics with numerous uses in HSD [24]. EMG is a bio-potential data collected by electrodes via the skin of a muscle fiber to monitor muscle function [25]. It is also linked to neurological data that travel from the spinal cord to the muscles [26]. The extraction of features and classification are the two elements of pattern recognition for EMG which are performed by the ML algorithm. The dimensionality of the EMG dataset was decreased to generate a feature vector in the feature extraction method [27]. This is beneficial for retrieving useful data and removing unnecessary information. These factors influence pattern recognition accuracy and categorization time. To preserve structural information, the features are recovered using segmentation of the EMG data rather than individual samples.

6) EYE-TRACKING

Eye-tracking technology is a rapidly expanding discipline that detects and analyzes human visual processing for interactive and diagnostic applications. Eye-tracking tools and techniques may be used in a variety of scientific fields, including HSD, to explore the quantitative data underpinning visual processes in an unobtrusive manner [28]. The eye tracker offers objective and quantitative proof of the user's visual and attentional processes in its diagnostic capacity. Eye movements are often collected in this capacity to determine the user's attentional patterns concerning a particular stimulus. The use of eye-tracking equipment in diagnostic applications is often inconspicuous. Furthermore, the projected stimulus is rarely required to vary or respond to the viewer's attention. The eye tracker is utilized in this scenario to record eye movements for post-trial, offline evaluation of the viewer's gaze during the experiment [29].

7) MAGNETIC RESONANCE IMAGING (MRI)

MRI is a technique that uses magnets and radio waves to create detailed images of the brain [30]. Along with detecting abnormalities, MRI also aids in determining the origin of the anomalies and consequently potential rehabilitation strategies. MRI can distinguish between opposing sides of the brain that are normally similar to determine which side and section of the brain are collapsing. Balafar *et al.* [31] investigated MRI image segmentation methodologies, imaging modalities, noise reduction, non-homogeneity correction, and segmentation algorithms. According to the study, MRI is capable of detecting anomalies in the brain at the seed stage and generally offers high-contrast brain images, outperforming computerized tomography (CT) scans. Various segmentation approaches have been considered, including fuzzy C-means, Gaussian mixture vector, learning vector quantization, self-organizing maps, watersheds, and others, many of which fail because of poor picture contrast, weak image borders, and unknown noise participation.

B. FEATURE EXTRACTION

To achieve higher accuracy, classification methods are crucial along with the selection of significant features. The acquired data were pre-processed to reduce noise and additional data amplification is required to complement data acquisition techniques. Electromyogram (EMG) artifacts and electrooculogram (EOG) artifacts are two of the most common artifacts observed when collecting EEG data. EMG noise is produced by muscle activation. EOG is produced every time the eyes move, even for basic responses such as blinking. Because EOG and EMG are 40–100 times stronger than EEG, they are easier to spot. To separate these aberrations, regression algorithms, which provide satisfactory EOG correction in both time and frequency domains, and spatial filtering, which can consistently filter out EOG and EMG data from EEG data obtained, can be used. Principal component analysis (PCA), independent component analysis, and dipole modeling are popular examples for feature selection [32]. If the characteristics are adequately extracted, the mental states can be successfully separated during the classification step. The popularity of non-invasive data acquisition techniques has left the work of data smoothing and filtering unfinished. Noise and artifacts are present in non-invasive data, and muscle action obstructs the data. The most common noise reduction techniques are listed below.

1) LINEAR FILTERING

It is typically employed to filter out noise in the form of analog data that are not in the brain's frequency range. Low-pass and high-pass linear filters are the two types of linear filters available. Minguillon *et al.* [33] emphasized the need for artifact removal in low-cost yet successful EEG data capture, as well as a review of existing artifact removal methods and their relevance. Exogenous (machinery faults) or endogenous (muscle, eye, or other cardiac activity- noise) sources produce artifacts. There are three ways to deal with artifacts in EEG data acquisition.

- Artifact avoidance: Avoid artifacts by following up on the subject's movements and the machine's operation.
- Artifact rejection: Contaminated experiments are discarded.
- Artifact removal: Pre-processing methods are used to remove artifacts.

2) ADAPTIVE FILTERING

The optimization theory underpins a linear adaptive filter. This filtering uses an adaptive approach to filter the collection of acquired data and regulate the adjustable parameters. It determines how the filter's design can be changed in response to any feature picked from the data under investigation. It is a two-stage closed-loop feedback system, with the first phase being selection and the second being cost function-based adaptation (which is the basis of the proper performance of a filter). The optimized cost function is supplied to an optimization algorithm, which updates the filter transfer function to attain the lowest cost for subsequent epochs. Nonlinear adaptive filtering techniques such as ANN, fuzzy logic, and GA lead to better solutions [34].

3) SPATIAL FILTERING

This is a supervised approach for reading EEG data using a minimal number of additional channels that are a linear mixture of the original channels. The goal is to break down a data into sub-components with the greatest possible inter-class difference [35].

4) MOVING AVERAGE ALGORITHM

The moving average algorithm is a well-known method for smoothing data. This method creates a new array of raw noisy data composed of equidistant points. The smoothing effect becomes more severe as the filter width increases.

5) DISCRETE WAVELET TRANSFORM (DWT)

DWT employs a spectral estimating approach that allows generic functions to be expressed as an endless series of wavelets [36]. It enables data analysis in a variety of frequency ranges and resolutions. Scaling and wavelet functions, which are related to low-pass and high-pass filters, respectively, were used to decompose the data. For the high-dimensional, multivariate series, Li [37] discussed the development of an accurate, efficient, and flexible classification system based on PCA. The multivariate time series (MTS) includes both time and variable-based dimensions, causing traditional classification approaches to fail. PCA is the most often used dimensionality reduction approach, as the principal component series has fewer dimensions than the original but retains most of the information about the original MTS.

6) FAST FOURIER TRANSFORM (FFT)

Power spectral density (PSD) estimation is used in FFT to assess the properties of the analog data [38]. The principal EEG spectra were found in the four frequency bands alpha, beta, gamma, and theta. To selectively represent the EEG sample data, PSD estimation was used to determine the characteristics of the obtained EEG data to be studied. The method has the advantages of being low-cost, simple to implement, sensible, and efficient. This is significant for practical BCI because of the high classification accuracy that comes with it [39].

7) WAVELET PACKET DECOMPOSITION (WPD)

Ting *et al.* [40] proposed employing a novel approach based on WPD to extract features from EEG data generated during a motor imagery task. WPD is more advanced than wavelet decomposition (WD) because it uses several bases. Different bases result in different categorization performances, which is an advantage. Because EEG data are non-stationary, established approaches such as the Fast Fourier Transform, auto regression model, time-frequency analysis, and wavelet transform are limited, prompting the invention of this unique method based on WPD.

C. DATA CLASSIFICATION

Any HSD system, particularly one designed for real-time applications, is strongly reliant on classification. Misclassification is often difficult with higher accuracy in the result. Effective, precise, and efficient categorization of extracted data is necessary to establish a high-performance system. Various methods have been developed to extract appropriate characteristics for classification from the acquired data are described below.

A generative classifier, such as Bayes quadratic, classifies a feature vector by selecting the class that best fits the feature vector [41]. SVM is a supervised learning model that knows how to categorize a feature vector [42]. During classification, a static classifier, such as a multilayer perceptron, cannot consider dynamic temporal information [43]. A dynamic classifier, such as a hidden Markov model, may adjust as the temporal dynamics change. The minor fluctuations in the training data set do not affect a stable classifier such as a linear discriminant analysis (LDA) [44]. An unstable classifier is sophisticated where minor changes in the learning set can result in significant structural changes because it does not know when to end training [45]. Recursive partitioning can be considered as an unstable classifier.

On the other hand, a normalized classifier can be considered more robust resulting in better performance. To bifurcate classes, these classifiers employ linear functions. SVM and LDA are examples of linear classifiers. Artificial neurons were used to create nonlinear boundaries. Neural networks are widely used for HSD, with MLP being the most prominent. Nonlinear Bayesian classifiers are generative, resulting in nonlinear decision-making limits because they are too slow for real-time HSD. Nearest neighbor classifiers, which are discriminative and simple, are applied to identify classifiers with nonlinear boundaries [46]. For enhancing classification, aggregating classifiers can be used as a modern and popular approach. Boosting, in which each classifier complements the previous one, voting, which is the most basic and popular, and stacking, in which the input to each meta-classifier is output from the preceding classifier are all examples of combination tactics [47]. Basic classification algorithms generate a single model from training data. A model's interpretation is very simple and has limits when it comes to reaching higher accuracy. In this scenario, a hybrid classifier is considered as a popular classifier because it mixes the outputs of many classifiers to meet the needs of the application [48].

III. METHOD

The SLR method is chosen to fulfill the study aim and answer the research questions among the many kinds of literature because it is a systematic and repeatable procedure [49]. The SLR approach is well known as a useful tool for assessing published work [50]. We have considered four stages of the Preferred Reporting Items for Systematic Reviews and Meta-Analysis (PRISMA) guidelines: identification, screening, eligibility, and final inclusion [51]. The overall flow of the procedure is shown in Fig. 2.

A. SEARCH AND SELECTION PROCESS

1) IDENTIFICATION STAGE

In this phase, a search and collection of articles are conducted appropriately. Twenty keywords are elicited from the research questions, and they are divided into four groups: Group A, Group B, Group C, and Group D (Table 1). Group A consists of general keywords of HF and HCI domains. Keywords related to the algorithms are considered in Group B. The human status-related keywords are pondered in Group C followed by the measuring tools in Group D. Searches from the databases are conducted using a combination of four keywords from different groupings and the "AND" operator.

For example, keyword combinations are selected such as "Human factors + Supervised learning + Physical workload + Physiological measures," and "Human-Computer Interaction + Machine learning + Cognitive load + Electroencephalography." Consequently, 600 keyword combinations are used to collect articles ($5 \times 5 \times 6 \times 4 = 600$). The resultant articles are accumulated after applying all the keyword combinations. Six thousand four hundred eighty-eight articles are gathered from the databases of three digital libraries (ScienceDirect: 2548; IEEE Xplore: 1061; ACM: 2879). The search and collecting processes are conducted in October 2021.

2) SCREENING STAGE

The screening procedure is divided into two phases. First, the reference management program "Mendeley" is used to remove duplicate data. After deleting duplicates from the 6488 articles, 2452 records remain. Then, using the following screening criteria, the titles and abstracts of the remaining articles are excluded: 1) publications that are not related to HSD, 2) articles that do not consider algorithms to analyze data, and 3) papers that are solely technical, analytical, and computer science in nature. A total of 2023 items are left after these two filtering procedures.

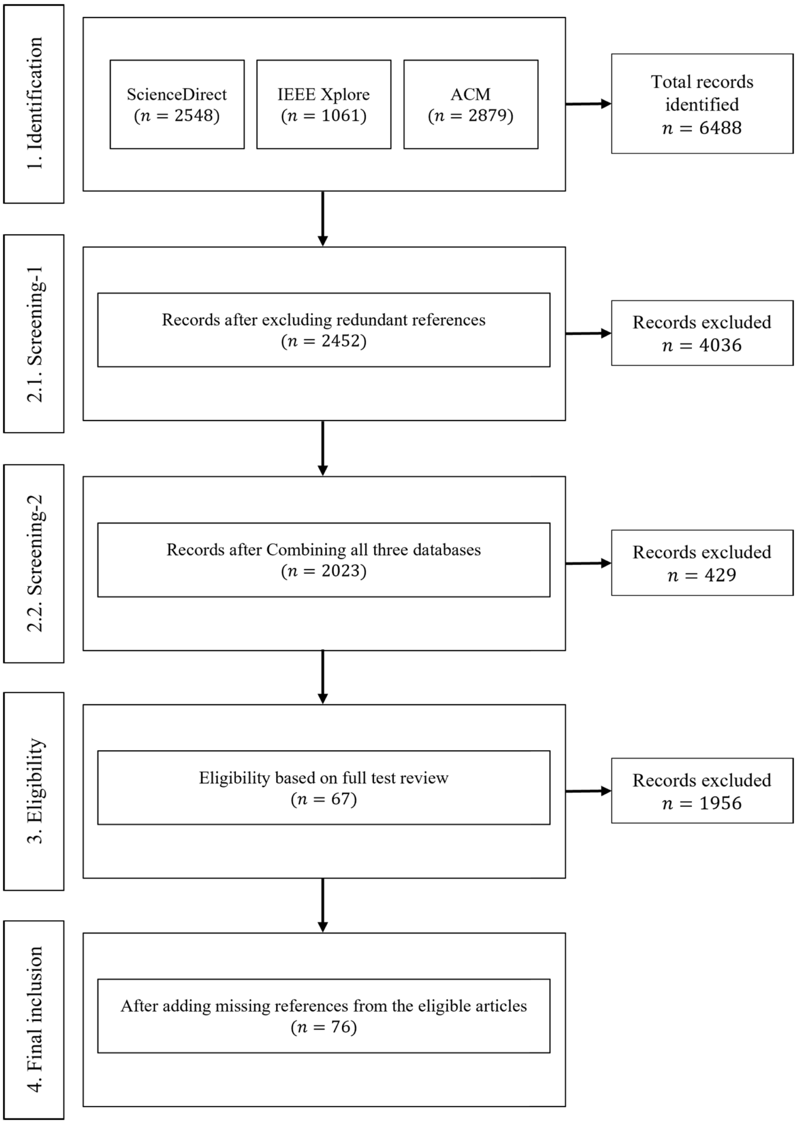

FIGURE 2. Flow diagram of systematic search and selection process.

TABLE 1. Keywords used for searching literature and selecting articles.

Group A	Group B	Group C	Group D
Human factors	Machine learning	Physical workload	Physiological measures
Ergonomics	Deep learning	Physical fatigue	Physiological methods
Human-computer interaction	Supervised learning	Mental workload	Electroencephalography (EEG)
User interface	Unsupervised learning	Cognitive fatigue	Electromyography (EMG)
User experience	Feature classification	Cognitive load	
		Stress	

3) ELIGIBILITY STAGE

In this stage, full-text articles are reviewed. 1956 articles that are not closely related to RQs are excluded. Sixty-seven records are selected to answer the RQs.

4) FINAL INCLUSION STAGE

The references of the remaining 67 papers are traversed during reviewing the articles at the eligibility stage. New articles are discovered that are missed by the search engine. These articles are incorporated, bringing the total number of records to 76.

B. DATA ANALYSIS AND STRATEGY

First, all the final selected articles are reviewed thoroughly, and based on the metadata gathered, a few graphs are plotted which open a new dimension for the researchers. To answer

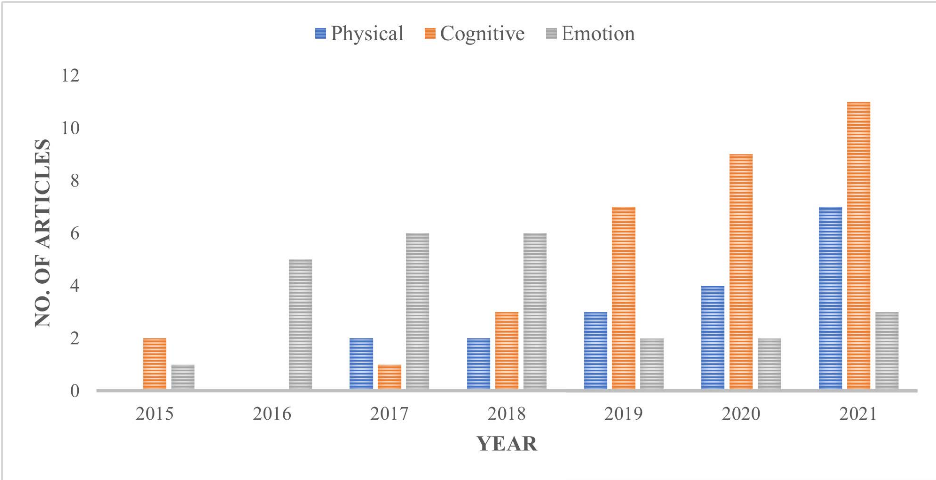

FIGURE 3. Representation of numbers of articles per year based on three categories.

RQ1, 76 articles are selected based on a two-step procedure. First, full articles are reviewed and their relevance to RQ1 is identified. Second, tables and graphs for the definitions and descriptions of functions, tasks, and information are created in the context of the RQ1. To answer RQ2, 69 articles are chosen using a two-step process. Primarily, selected articles are fully reviewed and their relevance to RQ2 is identified. In the review step, different data acquisition tools and their usage are comprehensively evaluated. Next, a table is created for the definition and description of the data acquisition tools. Additionally, the relationship between data type and data acquisition tools in the context of an HSD is established. To answer RQ3, 70 articles are distinctly reviewed based on the algorithms used to analyze the data and results. In the review step, selected articles are evaluated based on algorithm selection for different data types, selection of features, and performance accuracies. Accordingly, a table is presented along with a discussion to answer RQ3.

IV. RESULTS

The results are organized as follows. First, a metadata analysis is performed based on the initial implications that describe the impacts of data categories in terms of physical, cognitive, and emotional. Then, the results of the RQs are demonstrated by taking all the necessary records of selected articles.

A. METADATA ANALYSIS

Three categories are considered for HSD classification: physical, cognitive, and emotional. Year-wise metadata analysis is performed based on selected articles from 2015 to 2021 (Fig. 3). The blue bar represents the published articles per year on physical status whereas the orange bar represents the cognitive status. The emotion category is represented by a gray-colored bar. The results show that the total number of published articles on HSD has increased, with research on cognitive status having the highest trend in recent years.

Another metadata analysis is performed based on selected articles from 2015 to 2021. Fig. 4 represents two main categories of analysis: quantitative and qualitative. The orange line indicates the quantitative category whereas the qualitative category is indicated by the blue line. Based on the plotted graph of selected articles, it is clearly shown that the quantitative category has a much higher impact on current research than the qualitative category. This will be very helpful for fellow researchers in choosing analytical categories.

Data type is categorized into five segments based on the acquired data using different data acquisition tools. Five types of data from brain, heart, skin, muscle, and eye are represented by five different colors. As per the represented graph (Fig. 5), the data related to brain have the highest impact on research, as it is the largest region and is represented by the blue line. The second highest acquired data type is the heart, which is represented by the orange line.

B. RQ1: WHAT KIND OF DATA ARE COLLECTED FOR DETECTING HUMAN STATUS IN EXISTING RESEARCH?

The data collected for HSD are classified into two main categories: quantitative and qualitative. In the quantitative category, five main regions are used to collect data using different data acquisition tools: brain, heart, skin, muscle, and eye. In the qualitative category, two main regions are considered for collecting data: psychological measures and self-reported measures. Each region has different measurement parameters. Fig. 6 describes the classification of parameters for the physiological data.

C. RQ2: HOW ARE THE DATA COLLECTED USING DIFFERENT DATA ACQUISITION TOOLS FOR HUMAN STATUS DETECTION?

The data collection process is critical in all forms of research, but it is more important for human status data

FIGURE 4. Representation of articles per year based on Qualitative and Quantitative.

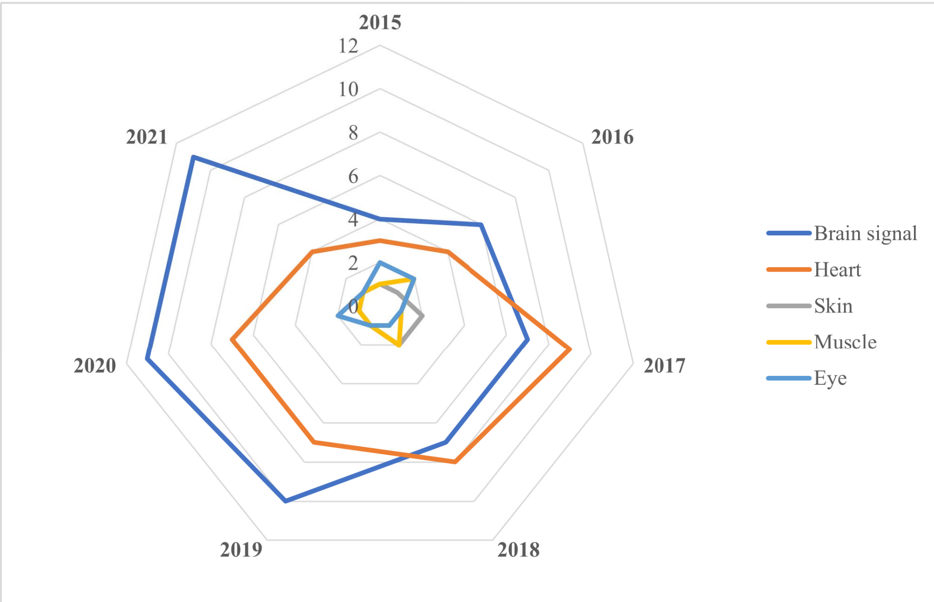

FIGURE 5. Year-wise trend based on measurement categories.

because the method must be error-free and the data must be free of noise to improve the accuracy of the algorithm. Table 2 presents some of the most frequently used devices for gathering human status data for the physical and cognitive followed by emotional category. As a result, a fast view of the devices is displayed, together with their physiological characteristics.

D. RQ3: WHAT TYPE OF MACHINE LEARNING AND DEEP LEARNING ALGORITHMS ARE APPLIED TO ANALYZE THE HUMAN STATUS DATA?

Data collected using different data acquisition tools are analyzed using different ML/DL algorithms. Feature extraction is performed first, and then classification is accomplished with significant algorithms for the efficiency of accuracy. HSD is performed for three categories: physical, cognitive, and emotional. Each category has a different data-collection method for the parameter. Wavelet coefficients are used to extract significant features, one of which is the modified wavelet energy parameter. To reduce redundancy and maximize relevance, maximum relevance (mRMR) is employed as the feature selection method. The results of the ML/DL techniques are described in Table 3 which implies that the suggested techniques have different performances in specific categories. Fig. 7 represents a combination of different methods and number of articles

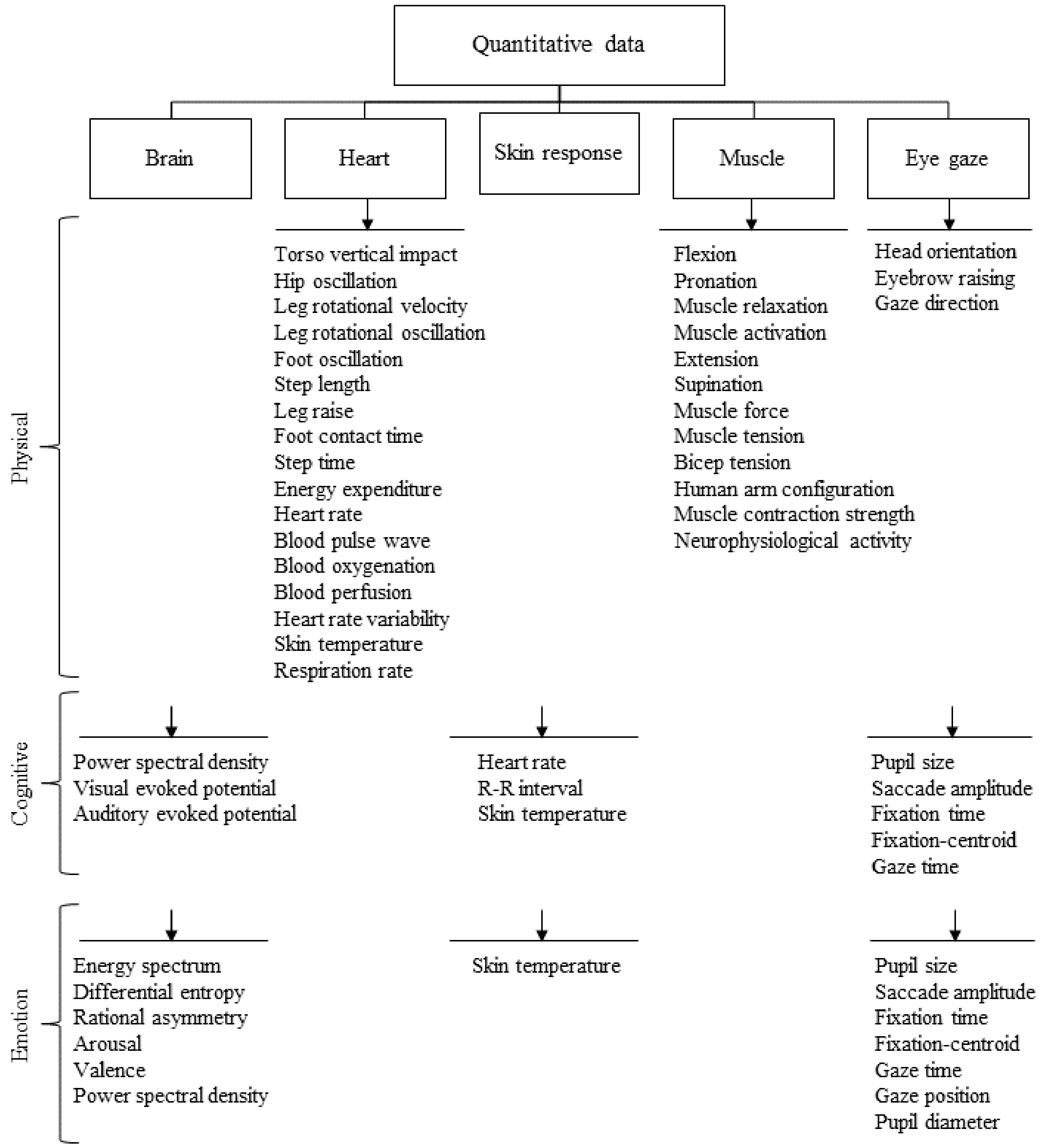

FIGURE 6. Classification of parameters for physiological data.

published. Depending on the features and nature of the data, two ML/DL methods are combined to obtain higher accuracy.

V. DISCUSSION

This study presents a novel, framework-driven examination of the data tying human aspects to detect human status- a topic that has received limited attention in the management literature so far. 76 journal articles are included in this SLR, which offer consistent and theoretically coherent different types of data on the influence of HSD (RQ1). All the publications show evidence that how the data is collected using different data collection tools that might result in higher influence for future studies (RQ2). In addition, several ML/DL algorithms are analyzed, and the performance accuracies show that the HSD has an intermediate human impact that might have a detrimental influence on performance (RQ3).

A. TYPES OF DATA FOR DETECTING HUMAN STATUS (RQ1)

The data gathered for HSD are categorized into two main categories with different measuring parameters. Figure 6 depicts the categorized parameters for collected physiological data. In the quantitative category, collecting brain data, most of the EEG research focused on frequency band analysis (i.e., the EEG data is decomposed into frequency bands: alpha, beta, gamma, delta, and theta, which are then analyzed for power differences). Several studies look at frequency band ratios, such as the alpha/beta ratio. In addition, a few research

TABLE 2. Data acquisition devices used to collect physiological data for physical, cognitive, and emotion categories.

Category	Data acquisition device	Reference
Physical	Shimmer3 (Shimmer technology)	[52]
	Neuronet 600 (Computational Diagnostics, Inc.)	[53]
	g.HIamp (g.tec medical engineering)	[54]
	Delsys EMG (Delsys)	[55]; [56]
	Xsens IMU (XSENS)	[57]
	Everion (Biovotion)	[58]
	eq02 LifeMonitor (Equivital)	[59]
	Myon 320 (myon AG)	[60]
	MP36 (BIOPAC Systems Inc.)	[61]
	Myo armband (Thalmic Labs)	[62]
	Neulog sensors (Neulog) Contec PM50 (Contec Medical Systems Co., Ltd.)	[63]
	Insight (Emotiv)	[64]
	Urbane 2 (LG)	[65]
	Mobi (TMSi) Kinect 3D (Microsoft)	[66]
	Polar H10 (Polar Electro)	[67]
	PhysioToolkit (PhysioNet)	[68]
Cognitive	Enobio 32 (Neuroelectrics)	[69]
	Twenty-two Ag/AgCl electrodes	[70]; [73]
	BioRadio 150 (Great Lakes NeuroTechnologies)	[71]
	Biosemi system (BioSemi B.V.)	[72]
	BrainAmp (Brain Vision)	[73]; [74]
	NeXus 10 MKII (Mind Media)	[75]
	HD-72 (Cognionics)	[76]
	Quik-Cap (Compumedics Neuroscan)	[77]
	Wearable contactable device	[78]
	Nuamps (Compumedics Neuroscan)	[79]
	Muse headband (InteraXon Inc.)	[80]
	MindWave (NeuroSky)	[81]; [82]
	Neurofax (Nihon Kohden Corporation)	[83]
	Band 2 (Microsoft Corporation)	[84]
	BioSemi headcap (BioSemi B.V.)	[85]
	B-Alert X-10 (Advanced Brain Monitoring, Inc.) Tobii X2-30 (Tobii)	[86]
	Versatile EEG (Bitbrain Technologies)	[87]
	EPOC (Emotiv)	[72]; [88]; [89]
Emotion	Kinect (Microsoft Corporation)	[90]
	RED500 (Imotions A/S)	[91]
	EPOC (Emotiv)	[92]; [93]
	PowerLab (ADInstruments)	[94]
	Q-sensor	[95]
	Mobile camera (iPhone 6S-Apple Inc.)	[96]
	FlexComp Infiniti (Thought Technology)	[97]
	ESI Neuro-Scan	[91]; [98]; [99]; [100]; [101]; [102]
	ActiveTwo system (BioSemi B.V.)	[90]; [94]; [98]; [101]; [103]; [104]; [105]; [106]; [107]

examine simple time-domain parameters such as data average and variance. A few research employ pre-built algorithms to analyze complex data (e.g., attention) presented by the EEG equipment.

Furthermore, eye blinking rate, or the number of blinks per minute, is employed as a characteristic in various research. Few studies look at interhemispheric differences (power disparities between the right and left hemispheres), while few look at non-directed functional connectivity measurements (i.e., statistical associations between spatially distinct brain areas). One research employs frequency band power cross-correlations between electrodes, while another uses phase-locking values, which measure phase synchronization between pairs of electrodes ([109]; [110]; [111]). The collected data, the BOLD contrast, is mentioned unambiguously in all fMRI experiments. Furthermore, studies employ directed functional connectivity measurements, in which temporal precedence information is used to discover the effect of brain areas and the direction of that influence [112].

Heart rate (HR), or the number of heartbeats per minute, and heart rate variability (HRV), or the fluctuations in the time intervals between successive heartbeats termed inter-beat intervals are used as parameters for heart data [113]. The gathered data is employed in the examined research, and metrics related to skin conductance level and skin conductance response are properly considered. A temperature sensor is also widely used in various experiments to assess skin temperature [114]. Neurophysiological activity is considered in physical measurements for muscle data. Muscle activation, extension, relaxation, muscle force, and strength are considered parameters for HSD under quantitative data collection [62].

TABLE 3. Significant algorithms with accuracy on performance.

Algorithm category	Method	Performance (%)			References
		Physical	Cognitive	Emotion	
Statistical method	Mean forecast error (MFE) Mean absolute deviation (MAD) Tracking signal (TS)		91.00		[108]
	Custom domain adaptation (CDA)		98.18		[77]
	Adaptive exponential smoothing (AES)		92.64		[83]
	Logistic regression (LR)	85.15	52.00	80.78 61.68	[64]; [84]; [95]; [102]
ML	Extreme learning machine (ELM)		95.00		[79]
	k-star	100			[68]
	Decision tree (DT)		95.90		[81]
	Random forest (RF)	88.80 76.06 80.00	56.00		[65]; [52]; [67]; [84]
	Support vector machine (SVM)	93.20 91.00 72.54 89.20 93.00 85.20	95.52 89.29 58.00 82.00 61.11	77.08 87.80 93.31 90.00 86.28 57.90 84.70 40.40 66.14 64.84 99.87	[59]; [61]; [62]; [63]; [66]; [64]; [72]; [79]; [84]; [90]; [88]; [91]; [107]; [100]; [95]; [98]; [93]; [97]; [99]; [102]; [104]; [96]
	Linear discriminant analysis (LDA)	84.12	66.67		[56]; [88]
	Long short-term memory (LSTM) DeepConvLSTM Bidirectional LSTM		91.54 94.66 86.33	62.50	[78]; [80]; [89]; [92]
	Artificial neural networks (ANN) Feed-forward neural network (FFNN) Probabilistic neural network (PNN)	95.80	52.00 91.80	56.20 96.00 75.00 80.00 91.20 86.75 75.00	[63]; [84]; [72]; [93]; [115]; [94]; [97]; [99]; [105]; [106]
	Naive bayes	96.00			[66]
DL	Convolutional neural network (CNN) Deep neural network (DNN) Convolutional recurrent attention model (CRAM) Graph convolutional neural network (GCNN)	82.30 97.84	94.41 73.11 99.79 91.54 94.66 95.05	90.63 98.47 47.67	[60]; [56]; [69]; [55]; [76]; [78]; [80]; [85]; [91]; [116]; [117]
	Deep kohonen neural network (DKNN)			98.00	[103]
	Deep belief network (DBN) Convolutional deep belief network (CDBN)		94.44	58.50	[88]; [90]

In the qualitative category, two types of measures are studied: psychological measures and self-reported measures. Questionnaire on gender, education, infection, age is considered under psychological measures whereas neurophysiological activities are considered as an important parameter for self-reported measures for HSD [66].

B. TOOLS USED TO COLLECT DATA FOR HSD (RQ2)

An overview of the data gathered for HSD using different data collection tools is represented in Table 2. For brain data, low-cost consumer-grade EEG devices are used mostly. The mostly used devices are ESI Neuro-Scan System [98] and Emotiv EPOC [72]. The ActiveTwo system [103] is also utilized mostly to gather data for the emotion category. Tobii Eye Tracker [86] is used for eye tracking and Myo armband [62] is used to get muscle data. The Shimmer3 [52] unit connects to one channel of galvanic skin response (GSR) data gathering and offers preamplification. Using the Shimmer ear clip or optical pulse probe, the GSR unit can measure the electrical properties or conductance of the skin, as well as capture an optical pulse data and convert it to estimate heart rate.

In addition to real-time data collection using different devices, qualitative data collection methods are also important for detecting human status. NASA task load index (NASA-TLX) is applied to measure physical [66] and cognitive [78] statuses where wechsler adult intelligence scale (WAIS) is included in some HSD studies [108] to measure intelligence and cognitive ability. In most of the controlled lab setups for inducing HSD, a biological phenomenon known as 'startle' (a quick reaction to a strong stimulus) occurs, which crosses various human body response systems: peripheral physiology, brain physiology, and behavior [118].

Algo.	CDA	LR	DT	RF	SVM	LDA	LSTM	ANN	NB	CNN	DNN	CRAM	DKNN	DBN
CDA	1													
LR		4				1								
DT			1											
RF				4	1									
SVM				1	22			4		3	1			
LDA		1				2								
LSTM							3			1				
ANN					4			10		2			1	
NB									1					
CNN					3		1	2		11	1	2		
DNN					1					1	1			
CRAM										2		1		
DKNN									1				1	
DBN														2

FIGURE 7. **Combination of algorithms on number of articles.**

As a result, dealing with this reaction when measuring data for HSD is an inherent barrier in laboratory experiments. However, when individuals fill out a self-report form, the researchers have the challenge of accurately capturing the amount of startle reaction.

1) ADVANTAGES AND DISADVANTAGES OF DATA COLLECTION METHODS FOR HSD

The advantages and disadvantages of acquired data as a medium for HSD are based on a review of previous work. The following are some of the benefits:

- Higher data accuracy than other modalities.
- Robustness.
- Delivering information on the state of operation.
- Tolerance for physical or mental impairments.
- Magnificent effectiveness on results.
- Not too invasive.
- Providing a neutral evaluation.
- Allowing for quick data collection.
- Resulting in real data that has been unmasked.

The disadvantages are mentioned below:

- Complex data processing techniques.
- Difficult in developing models.
- Connectivity concerns in data acquisition.
- Resulting data errors.
- Adding non-stationary nature to overall complexity.
- Complicated data collection process.
- Different impedance levels on data processing.
- Training and test data may not be in synchronization.
- Mismatch in the subject distribution.

C. PERFORMANCE OF ML/DL ALGORITHMS FOR HSD (RQ3)

The linear and non-linear analysis of characteristics selected from the obtained data is undertaken to evaluate human status. The data are classified using popular ML algorithms like logistic regression, naive bayes, k-nearest neighbors, decision tree, and support vector machine (Table 3). HSD does not rely on sampling from the general population and invariably results in changed physiological data [119]. Successful experimentation on the new strategy of merging several data sources is accomplished in a classic work. As a result, a wide range of data is captured in real-time, including acceleration, electrodermal activity, heart rate, skin response, eye gaze data. A brief introduction of various ML algorithms is provided below.

Statistical approaches to measuring forecast accuracy custom domain adaptation (CDA) obtains higher accuracy of 98.18% [77] where mean forecast error (MFE) and mean absolute deviation (MAD) give an accuracy of 91% in cognitive load measurement [108]. An accuracy of 100% is achieved under the physical category by k-star which is an instance-based regressing method, where the estimation for a given input is calculated from samples [68]. Logistic regression (LR) is used for the emotional category, and it achieved higher accuracy of 80.78% [95].

ML algorithms are the most effective, accurate, and efficient classification algorithms of extracted data with higher performance for HSD. Support vector machine (SVM) is a highly effective classifier because of its training speed, indifference to overtraining, robustness, and ability to overcome the dimensionality curse [42]. Using SVM for classification, an experiment on emotion detection module is conducted considering speech and image data, with promising results of 99.87% [96]. High-dimensional feature space, on the other hand, might leads to larger SVM generalization mistakes [120]. For the physical category, SVM achieves the highest accuracy of 93.20% where physical exertion modeling is conducted using multiple physiological measures [59]. For decoding motor and mental imaginary, an accuracy of 95.52% is achieved using SVM under the cognitive category [72]. SVM's generalization performance is better than other classifiers because it divides the whole space into sample subspaces. An accuracy of 94.66% is achieved using long short-term memory (LSTM) [80] for the cognitive category and 84.12% accuracy is achieved by linear discriminant analysis (LDA) for the physical category [56].

Random forest (RF) combines classification, regression, density estimation, manifold learning, semi-supervised learning, and active learning into a single framework [121]. These employ bootstrapping to sample the provided dataset and pick a portion of characteristics to disperse the tree's nodes, injecting unpredictability into the output from individual trees. These classifiers are resilient and excellent at handling outliers because of randomization, making them excellent for real-time HSD [122]. An accuracy of 88.80% [65] is achieved using an RF classifier for the physical category whereas cognitive obtains an accuracy of 56% [84]. Artificial neural networks (ANN) based classifier feed-forward neural network (FFNN) gives 95.80% accuracy for physical category [63]. EEG-based emotion recognition using wavelets achieve the highest accuracy of 91.20% [99]. Each neuron in an ANN is modeled after the neurons in a real neural network, and the right design of which can lead to the construction of a good classifier [43].

DL has proven to be a particularly useful technique in recent decades due to its ability to manage large volumes of data. Hidden layers have eclipsed traditional approaches in popularity, particularly in pattern recognition. Convolutional neural networks (CNN) are one of the most often used deep neural networks [123]. An accuracy of 99.79% is achieved by applying CNN under the cognitive category [76] and 97.84% for physical [56]. Deep neural network (DNN), convolutional recurrent attention model (CRAM), and graph convolutional neural network (GCNN) achieve prominent average efficiencies of different datasets, respectively, which both receive better performances than most of the compared studies.

D. THEORETICAL CHALLENGES

As with any review, the obstacles faced lead to a variety of restrictions, such as study selection, relevant information selection, and findings presentation, analysis, generalization, and implication. The availability of studies addressing specific components of the HSD limits the outcomes of a review. This raises the possibility that more research factors have yet to be investigated, as well as the possibility that the number of research reporting a certain research finding is not necessarily connected to its relevance. Another prevalent restriction is the risk of missing some important material that does not meet the systematic extraction requirements or is missed by the keywords. This may be because the search considers broad topics and associates academic disciplines. However, given the substantial body of data that supports the theoretical framework offered, this is unlikely to have a major impact on findings.

E. APPLICATION

In many instances, ML works effectively as long as there is a correlation between the job at hand and the availability of data. ML has infiltrated many other sectors, including medical, pharmacy, law, business, finance, art, agriculture, photography, sports, education, media, military, and politics, due to the ability to make choices or predictions based on data. The wide spectrum of applications under HSD covers intelligent tutoring [115], virtual reality [124], medical diagnosis [125], automobile industry [126], robotics [127], and decision support [128].

VI. CONCLUSION

HSD is a psycho-physiological response to everyday occurrences. There are several studies available that have conducted research in a controlled laboratory environment and shown excellent performance in terms of accuracy in detecting human status. Many devices are now available on the market that may be used to collect physiological data. These devices are simple to operate and produce minimal noise and errors. As a result, they may be used to evaluate and measure human status without interfering with the user's normal activities. The raw data are then pre-processed by employing filters to remove artifacts and noise, followed by feature extraction and selection. To create classification models, a variety of machine learning techniques are used. The ultimate goal of HSD is to create a model with incredible accuracy that is both effective and economical. In this study, a systematic literature review is conducted to understand the significance of ML methods in HSD. This review provided here summarized key details from earlier research, including device names, evaluation measures, methodologies employed, advantages, limits, and applications. This research will undoubtedly assist fellow researchers in gaining a thorough understanding of HSD in physical, cognitive, and emotional categories.

REFERENCES

[1] S. R. Hong, J. Hullman, and E. Bertini, "Human factors in model interpretability: Industry practices, challenges, and needs," in *Proc. ACM Hum.-Comput. Interact.*, May 2020, vol. 4, no. CSCW1, pp. 1–26.

[2] A. D. Jurik and A. C. Weaver, "Body sensors: Wireless access to physiological data," *IEEE Softw.*, vol. 26, no. 1, pp. 71–73, Jan. 2009.

[3] M. Viceconti, P. Hunter, and R. Hose, "Big data, big knowledge: Big data for personalized healthcare," *IEEE J. Biomed. Health Informat.*, vol. 19, no. 4, pp. 1209–1215, Jul. 2015.

[4] S. S. Grigsby, "Artificial intelligence for advanced human-machine symbiosis," in *Proc. Int. Conf. Augmented Cognition*. Cham, Switzerland: Springer, 2018, pp. 255–266.

[5] B. Rush, L. A. Celi, and D. J. Stone, "Applying machine learning to continuously monitored physiological data," *J. Clin. Monitor. Comput.*, vol. 33, no. 5, pp. 887–893, Oct. 2019.

[6] J.-Y. Zhang, S.-L. Liu, Q.-M. Feng, J.-Q. Gao, and Q. Zhang, "Correlative evaluation of mental and physical workload of laparoscopic surgeons based on surface electromyography and eye-tracking signals," *Sci. Rep.*, vol. 7, no. 1, pp. 1–7, Dec. 2017.

[7] K. Ochsner and J. Gross, "The cognitive control of emotion," *Trends Cognit. Sci.*, vol. 9, no. 5, pp. 242–249, May 2005.

[8] T. I. Voznenko, E. V. Chepin, and G. A. Urvanov, "The control system based on extended BCI for a robotic wheelchair," *Proc. Comput. Sci.*, vol. 123, pp. 522–527, Dec. 2018.

[9] R. K. Chaurasiya, N. D. Londhe, and S. Ghosh, "An efficient P300 speller system for brain-computer interface," in *Proc. Int. Conf. Signal Process., Comput. Control (ISPCC)*, Sep. 2015, pp. 57–62.

[10] T. I. Voznenko, G. A. Urvanov, A. A. Dyumin, S. V. Andrianova, and E. V. Chepin, "The research of emotional state influence on quality of a brain-computer interface usage," *Proc. Comput. Sci.*, vol. 88, pp. 391–396, Jan. 2016.

[11] J. Kim, M.-K. Kim, and S.-P. Kim, "Development of passive BCIs for user-state monitoring with smart IT systems," in *Proc. 18th IEEE Int. Symp. Consum. Electron. (ISCE)*, Jun. 2014, pp. 1–2.

[12] H. Jing, T.-Y. Hu, H.-S. Lee, W.-C. Chen, C.-C. Lee, Y. Tsao, and H.-M. Wang, "Ensemble of machine learning algorithms for cognitive and physical speaker load detection," in *Proc. Interspeech*, Sep. 2014, pp. 447–451.

[13] J. Allanson and S. H. Fairclough, "A research agenda for physiological computing," *Interacting Comput.*, vol. 16, no. 5, pp. 857–878, Oct. 2004.

[14] C. Brunner, G. Andreoni, L. Bianchi, B. Blankertz, C. Breitwieser, S. I. Kanoh, C. A. Kothe, A. Lécuyer, S. Makeig, J. Mellinger, and P. Perego, "BCI software platforms," in *Towards Practical Brain-Computer Interfaces*. Berlin, Germany: Springer, 2012, pp. 303–331.

[15] C. Guger, G. Edlinger, W. Harkam, I. Niedermayer, and G. Pfurtscheller, "How many people are able to operate an EEG-based brain-computer interface (BCI)?" *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 11, no. 2, pp. 145–147, Jun. 2003.

[16] F. A. Mousa, R. A. El-Khoribi, and M. E. Shoman, "A novel brain computer interface based on principle component analysis," *Proc. Comput. Sci.*, vol. 82, pp. 49–56, Jan. 2016.

[17] R. Sitaram, N. Weiskopf, A. Caria, R. Veit, M. Erb, and N. Birbaumer, "fMRI brain-computer interfaces," *IEEE Signal Process. Mag.*, vol. 25, no. 1, pp. 95–106, Dec. 2007.

[18] A. M. Dale and R. L. Buckner, "Selective averaging of rapidly presented individual trials using fMRI," *Hum. Brain Mapping*, vol. 5, no. 5, pp. 329–340, 1997.

[19] R. A. Ramadan and A. V. Vasilakos, "Brain computer interface: Control signals review," *Neurocomputing*, vol. 223, pp. 26–44, Feb. 2017.

[20] J. Kang, "Signal acquisition in brain-computer interface," Univ. Auckland, Auckland, New Zealand, Tech. Rep., 2017.

[21] A. L. Goldberger and E. Gold-berger, "Clinical electrocardiography, a simplified approach," *Crit. Care Med.*, vol. 9, no. 12, pp. 891–892, 1981.

[22] F. Sufi, I. Khalil, and J. Hu, "ECG-based authentication," in *Handbook of Information and Communication Security*. Berlin, Germany: Springer, 2010, pp. 309–331.

[23] J. P. Martínez, R. Almeida, S. Olmos, A. P. Rocha, and P. Laguna, "A wavelet-based ECG delineator: Evaluation on standard databases," *IEEE Trans. Biomed. Eng.*, vol. 51, no. 4, pp. 570–581, Apr. 2004.

[24] M. B. I. Reaz, M. S. Hussain, and F. Mohd-Yasin, "Techniques of EMG signal analysis: Detection, processing, classification and applications," *Biol. Procedures*, vol. 8, no. 1, pp. 11–35, Dec. 2006.

[25] D. Stashuk, "EMG signal decomposition: How can it be accomplished and used?" *J. Electromyogr. Kinesiol.*, vol. 11, no. 3, pp. 151–173, 2001.

[26] R. Merletti and L. R. L. Conteab, "Surface EMG signal processing during isometric contractions," *J. Electromyogr. Kinesiol.*, vol. 7, no. 4, pp. 241–250, 1997.

[27] H. Huang, P. Zhou, G. Li, and T. A. Kuiken, "An analysis of EMG electrode configuration for targeted muscle reinnervation based neural machine interface," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 16, no. 1, pp. 37–45, Feb. 2008.

[28] M. L. Mele and S. Federici, "Gaze and eye-tracking solutions for psychological research," *Cognit. Process.*, vol. 13, no. 1, pp. 261–265, Aug. 2012.

[29] A. T. Duchowski, "A breadth-first survey of eye-tracking applications," *Behav. Res. Methods, Instrum., Comput.*, vol. 34, no. 4, pp. 455–470, Nov. 2002.

[30] R. W. Brown, Y. C. N. Cheng, E. M. Haacke, M. R. Thompson, and R. Venkatesan, *Magnetic Resonance Imaging: Physical Principles and Sequence Design*. Hoboken, NJ, USA: Wiley, 2014.

[31] M. A. Balafar, A. R. Ramli, M. I. Saripan, and S. Mashohor, "Review of brain MRI image segmentation methods," *Artif. Intell. Rev.*, vol. 33, no. 3, pp. 261–274, Mar. 2010.

[32] D. V. Moretti, F. Babiloni, F. Carducci, F. Cincotti, E. Remondini, P. M. Rossini, S. Salinari, and C. Babiloni, "Computerized processing of EEG–EOG–EMG artifacts for multi-centric studies in EEG oscillations and event-related potentials," *Int. J. Psychophysiol.*, vol. 47, no. 3, pp. 199–216, Mar. 2003.

[33] J. Minguillon, M. A. Lopez-Gordo, and F. Pelayo, "Trends in EEG-BCI for daily-life: Requirements for artifact removal," *Biomed. Signal Process. Control*, vol. 31, pp. 407–418, Jan. 2017.

[34] G. C. Goodwin and K. S. Sin, *Adaptive Filtering Prediction and Control*. Chelmsford, MA, USA: Courier Corporation, 2014.

[35] D. Wu, J.-T. King, C.-H. Chuang, C.-T. Lin, and T.-P. Jung, "Spatial filtering for EEG-based regression problems in brain–computer interface (BCI)," *IEEE Trans. Fuzzy Syst.*, vol. 26, no. 2, pp. 771–781, Apr. 2017.

[36] M. J. Shensa, "The discrete wavelet transform: Wedding the a trous and Mallat algorithms," *IEEE Trans. Signal Process.*, vol. 40, no. 10, pp. 2464–2482, Oct. 2001.

[37] H. Li, "Accurate and efficient classification based on common principal components analysis for multivariate time series," *Neurocomputing*, vol. 171, pp. 744–753, Jan. 2016.

[38] C. Van Loan, *Computational Frameworks for the Fast Fourier Transform*. Philadelphia, PA, USA: SIAM, 1992.

[39] Y. Wang, Z. Zhang, Y. Li, X. Gao, S. Gao, and F. Yang, "BCI competition 2003-data set IV: An algorithm based on CSSD and FDA for classifying single-trial EEG," *IEEE Trans. Biomed. Eng.*, vol. 51, no. 6, pp. 1081–1086, Jun. 2004.

[40] W. Ting, Y. Guo-Zheng, Y. Bang-Hua, and S. Hong, "EEG feature extraction based on wavelet packet decomposition for brain computer interface," *Measurement*, vol. 41, no. 6, pp. 618–625, Jul. 2008.

[41] F. Lotte, M. Congedo, A. Lécuyer, F. Lamarche, and B. Arnaldi, "A review of classification algorithms for EEG-based brain-computer interfaces," *J. Neuron Eng.*, vol. 4, no. 2, p. R1, 2007.
[42] C. Cortes and V. Vapnik, "Support-vector networks," *Mach. Learn.*, vol. 20, no. 3, pp. 273–297, Sep. 1997.
[43] F. Rosenblatt, "The perceptron: A probabilistic model for information storage and organization in the brain," *Psychol. Rev.*, vol. 65, no. 6, p. 386, 1958.
[44] R. A. Fisher, "The use of multiple measurements in taxonomic problems," *Ann. Eugenics*, vol. 7, no. 2, pp. 179–188, Aug. 2012.
[45] W. D. Shannon and D. Banks, "Combining classification trees using MLE," *Statist. Med.*, vol. 18, no. 6, pp. 727–740, Mar. 1999.
[46] L. I. Kuncheva and L. C. Jain, "Nearest neighbor classifier: Simultaneous editing and feature selection," *Pattern Recognit. Lett.*, vol. 20, nos. 11–13, pp. 1149–1156, Nov. 1999.
[47] A. Bablani, D. R. Edla, D. Tripathi, and V. Kuppili, "An efficient concealed information test: EEG feature extraction and ensemble classification for lie identification," *Mach. Vis. Appl.*, vol. 30, no. 5, pp. 813–832, Jul. 2019.
[48] T.-T. Wong, N.-Y. Yang, and G.-H. Chen, "Hybrid classification algorithms based on instance filtering," *Inf. Sci.*, vol. 520, pp. 445–455, May 2020.
[49] F. Pearson, "Systematic approaches to a successful literature review," *Educ. Psychol. Pract.*, vol. 30, no. 2, pp. 205–206, Apr. 2014.
[50] J. R. Cooper, "A multidimensional approach to the adoption of innovation," *Manage. Decis.*, vol. 36, no. 8, pp. 493–502, Oct. 1998.
[51] D. Moher, A. Liberati, J. Tetzlaff, D. G. Altman, and G. Prisma, "Preferred reporting items for systematic reviews and meta-analyses: The PRISMA statement," *Ann. Internal Med.*, vol. 151, no. 4, pp. 264–269, 2009.
[52] Z. S. Maman, Y.-J. Chen, A. Baghdadi, S. Lombardo, L. A. Cavuoto, and F. M. Megahed, "A data analytic framework for physical fatigue management using wearable sensors," *Expert Syst. Appl.*, vol. 155, Oct. 2020, Art. no. 113405.
[53] X. Zha, L. Wehbe, R. J. Sclabassi, Z. Mace, Y. V. Liang, A. Yu, J. Leonardo, B. C. Cheng, T. A. Hillman, D. A. Chen, and C. N. Riviere, "A deep learning model for automated classification of intraoperative continuous EMG," *IEEE Trans. Med. Robot. Bionics*, vol. 3, no. 1, pp. 44–52, Feb. 2021.
[54] A. Ameri, M. A. Akhaee, E. Scheme, and K. Englehart, "A deep transfer learning approach to reducing the effect of electrode shift in EMG pattern recognition-based control," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 28, no. 2, pp. 370–379, Feb. 2019.
[55] J. Zhang, C. Ling, and S. Li, "EMG signals based human action recognition via deep belief networks," *IFAC-PapersOnLine*, vol. 52, no. 19, pp. 271–276, 2019.
[56] R. Rajapriya, K. Rajeswari, and S. J. Thiruvengadam, "Deep learning and machine learning techniques to improve hand movement classification in myoelectric control system," *Biocybernetics Biomed. Eng.*, vol. 41, no. 2, pp. 554–571, Apr. 2021.
[57] Y. Jiang, P. Malliaras, B. Chen, and D. Kulić, "Model-based data augmentation for user-independent fatigue estimation," *Comput. Biol. Med.*, vol. 137, Oct. 2021, Art. no. 104839.
[58] M. Soto, C. Satterfield, T. Fritz, G. C. Murphy, D. C. Shepherd, and N. Kraft, "Observing and predicting knowledge worker stress, focus and awakeness in the wild," *Int. J. Hum.-Comput. Stud.*, vol. 146, Feb. 2021, Art. no. 102560.
[59] W. Umer, H. Li, Y. Yantao, M. F. Antwi-Afari, S. Anwer, and X. Luo, "Physical exertion modeling for construction tasks using combined cardiorespiratory and thermoregulatory measures," *Autom. Construct.*, vol. 112, Apr. 2020, Art. no. 103079.
[60] A. Moniri, D. Terracina, J. Rodriguez-Manzano, P. H. Strutton, and P. Georgiou, "Real-time forecasting of sEMG features for trunk muscle fatigue using machine learning," *IEEE Trans. Biomed. Eng.*, vol. 68, no. 2, pp. 718–727, Feb. 2021.
[61] P. A. Karthick, D. M. Ghosh, and S. Ramakrishnan, "Surface electromyography based muscle fatigue detection using high-resolution time-frequency methods and machine learning algorithms," *Comput. Methods Programs Biomed.*, vol. 154, pp. 45–56, Feb. 2018.
[62] Y. Li, W. Zhang, Q. Zhang, and N. Zheng, "Transfer learning-based muscle activity decoding scheme by low-frequency sEMG for wearable low-cost application," *IEEE Access*, vol. 9, pp. 22804–22815, 2021.
[63] A. O. Akmandor and N. K. Jha, "Keep the stress away with SoDA: Stress detection and alleviation system," *IEEE Trans. Multi-Scale Comput. Syst.*, vol. 3, no. 4, pp. 269–282, Oct. 2017.
[64] S. M. U. Saeed, S. M. Anwar, H. Khalid, M. Majid, and U. Bagci, "EEG based classification of long-term stress using psychological labeling," *Sensors*, vol. 20, no. 7, p. 1886, Mar. 2020.
[65] B. Egilmez, E. Poyraz, W. Zhou, G. Memik, P. Dinda, and N. Alshurafa, "UStress: Understanding college Student subjective stress using wrist-based passive sensing," in *Proc. IEEE Int. Conf. Pervasive Comput. Commun. Workshops (PerCom Workshops)*, Mar. 2017, pp. 673–678.
[66] A. Alberdi, A. Aztiria, A. Basarab, and D. J. Cook, "Using smart offices to predict occupational stress," *Int. J. Ind. Ergonom.*, vol. 67, pp. 13–26, Sep. 2018.
[67] C. Chen, C. Li, C.-W. Tsai, and X. Deng, "Evaluation of mental stress and heart rate variability derived from wrist-based photoplethysmography," in *Proc. IEEE Eurasia Conf. Biomed. Eng., Healthcare Sustainability (ECBIOS)*, May 2019, pp. 65–68.
[68] I. Bichindaritz, C. Breen, E. Cole, N. Keshan, and P. Parimi, "Feature selection and machine learning based multilevel stress detection from ECG signals," in *Proc. Int. Conf. Innovation Med. Healthcare*. Springer, 2017, pp. 202–213.
[69] Y. Wang, Y. Shi, J. Du, Y. Lin, and Q. Wang, "A CNN-based personalized system for attention detection in wayfinding tasks," *Adv. Eng. Informat.*, vol. 46, Oct. 2020, Art. no. 101180.
[70] D. Zhang, L. Yao, K. Chen, and J. Monaghan, "A convolutional recurrent attention model for subject-independent EEG signal analysis," *IEEE Signal Process. Lett.*, vol. 26, no. 5, pp. 715–719, May 2019.
[71] S. Kumar and F. Sahin, "A framework for a real time intelligent and interactive brain computer interface," *Comput. Electr. Eng.*, vol. 43, pp. 193–214, Apr. 2015.
[72] M. T. Sadiq, X. Yu, Z. Yuan, M. Z. Aziz, S. Siuly, and W. Ding, "A matrix determinant feature extraction approach for decoding motor and mental imagery EEG in subject-specific tasks," *IEEE Trans. Cognit. Develop. Syst.*, vol. 14, no. 2, pp. 375–387, Jun. 2022.
[73] D. Li, J. Xu, J. Wang, X. Fang, and Y. Ji, "A multi-scale fusion convolutional neural network based on attention mechanism for the visualization analysis of EEG signals decoding," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 28, no. 12, pp. 2615–2626, Dec. 2020.
[74] O. Y. Kwon, M. H. Lee, C. Guan, and S. W. Lee, "Subject-independent brain-computer interfaces based on deep convolutional neural networks," *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 31, no. 10, pp. 3839–3852, Oct. 2019.
[75] T. Ishida and H. Uwano, "Time series analysis of programmer's EEG for debug state classification," in *Proc. 3rd Int. Conf. Art, Sci., Eng. Program.*, Apr. 2019, pp. 1–7.
[76] M. Wang, H. El-Fiqi, J. Hu, and H. A. Abbass, "Convolutional neural networks using dynamic functional connectivity for EEG-based person identification in diverse human states," *IEEE Trans. Inf. Forensics Security*, vol. 14, no. 12, pp. 3259–3272, Dec. 2019.
[77] M. Jiménez-Guarneros and P. Gómez-Gil, "Custom domain adaptation: A new method for cross-subject, EEG-based cognitive load recognition," *IEEE Signal Process. Lett.*, vol. 27, pp. 750–754, 2020.
[78] E. Q. Wu, P. Xiong, Z.-R. Tang, G.-J. Li, A. Song, and L.-M. Zhu, "Detecting dynamic behavior of brain fatigue through 3-D-CNN-LSTM," *IEEE Trans. Syst., Man, Cybern., Syst.*, vol. 52, no. 1, pp. 90–100, Jan. 2021.
[79] J. Chen, H. Wang, and C. Hua, "Electroencephalography based fatigue detection using a novel feature fusion and extreme learning machine," *Cognit. Syst. Res.*, vol. 52, pp. 715–728, Dec. 2018.
[80] A. Salehzadeh, A. P. Calitz, and J. Greyling, "Human activity recognition using deep electroencephalography learning," *Biomed. Signal Process. Control*, vol. 62, Sep. 2020, Art. no. 102094.
[81] F.-R. Lin and C.-M. Kao, "Mental effort detection using EEG data in E-learning contexts," *Comput. Educ.*, vol. 122, pp. 63–79, Jul. 2018.
[82] T. Zhang, R. Fruchter, and M. Frank, "Are they paying attention? A model-based method to identify individuals' mental states," *Computer*, vol. 50, no. 3, pp. 40–49, Mar. 2017.

[83] J. Zhang, Z. Yin, and R. Wang, ''Recognition of mental workload levels under complex human–machine collaboration by using physiological features and adaptive support vector machines,'' *IEEE Trans. Human-Mach. Syst.*, vol. 45, no. 2, pp. 200–214, Apr. 2014.

[84] V. Borisov, E. Kasneci, and G. Kasneci, ''Robust cognitive load detection from wrist-band sensors,'' *Comput. Hum. Behav. Rep.*, vol. 4, Aug. 2021, Art. no. 100116.

[85] R. Sahay and C. G. Brinton, ''Robust subject-independent P300 waveform classification via signal pre-processing and deep learning,'' *IEEE Access*, vol. 9, pp. 87579–87591, 2021.

[86] G. Makransky, T. S. Terkildsen, and R. E. Mayer, ''Role of subjective and objective measures of cognitive processing during learning in explaining the spatial contiguity effect,'' *Learn. Instruct.*, vol. 61, pp. 23–34, Jun. 2019.

[87] L. Cabañero Gómez, R. Hervás, I. González, and V. Villarreal, ''Studying the generalisability of cognitive load measured with EEG,'' *Biomed. Signal Process. Control*, vol. 70, Sep. 2021, Art. no. 103032.

[88] N. E. Elsayed, A. S. Tolba, M. Z. Rashad, T. Belal, and S. Sarhan, ''A deep learning approach for brain computer interaction-motor execution EEG signal classification,'' *IEEE Access*, vol. 9, pp. 101513–101529, 2021.

[89] D. Das Chakladar, S. Dey, P. P. Roy, and D. P. Dogra, ''EEG-based mental workload estimation using deep BLSTM-LSTM network and evolutionary algorithm,'' *Biomed. Signal Process. Control*, vol. 60, Jul. 2020, Art. no. 101989.

[90] H. Ranganathan, S. Chakraborty, and S. Panchanathan, ''Multimodal emotion recognition using deep learning architectures,'' in *Proc. IEEE Winter Conf. Appl. Comput. Vis. (WACV)*, Mar. 2016, pp. 1–9.

[91] M. Zhao, H. Gao, W. Wang, and J. Qu, ''Research on human-computer interaction intention recognition based on EEG and eye movement,'' *IEEE Access*, vol. 8, pp. 145824–145832, 2020.

[92] D. Li, Z. Wang, C. Wang, S. Liu, W. Chi, E. Dong, X. Song, Q. Gao, and Y. Song, ''The fusion of electroencephalography and facial expression for continuous emotion recognition,'' *IEEE Access*, vol. 7, pp. 155724–155736, 2019.

[93] R. M. Mehmood and H. J. Lee, ''A novel feature extraction method based on late positive potential for emotion recognition in human brain signal patterns,'' *Comput. Electr. Eng.*, vol. 53, pp. 444–457, Jul. 2016.

[94] A. Goshvarpour, A. Abbasi, and A. Goshvarpour, ''An accurate emotion recognition system using ECG and GSR signals and matching pursuit method,'' *Biomed. J.*, vol. 40, no. 6, pp. 355–368, 2017.

[95] H. Feng, H. M. Golshan, and M. H. Mahoor, ''A wavelet-based approach to emotion classification using EDA signals,'' *Expert Syst. Appl.*, vol. 112, pp. 77–86, Dec. 2018.

[96] M. S. Hossain and G. Muhammad, ''Emotion-aware connected healthcare big data towards 5G,'' *IEEE Internet Things J.*, vol. 5, no. 4, pp. 2399–2406, Aug. 2017.

[97] M. Khezri, M. Firoozabadi, and A. R. Sharafat, ''Reliable emotion recognition system based on dynamic adaptive fusion of forehead biopotentials and physiological signals,'' *Comput. Methods Programs Biomed.*, vol. 122, no. 2, pp. 149–164, Nov. 2015.

[98] Y. Zhang, S. Zhang, and X. Ji, ''EEG-based classification of emotions using empirical mode decomposition and autoregressive model,'' *Multimedia Tools Appl.*, vol. 77, no. 20, pp. 26697–26710, Oct. 2018.

[99] S. Thejaswini, K. M. R. Kumar, S. Rupali, and V. Abijith, ''EEG based emotion recognition using wavelets and neural networks classifier,'' in *Cognitive Science and Artificial Intelligence*. Singapore: Springer, 2018, pp. 101–112.

[100] S. Liu, J. Tong, J. Meng, J. Yang, X. Zhao, F. He, H. Qi, and D. Ming, ''Study on an effective cross-stimulus emotion recognition model using EEGs based on feature selection and support vector machine,'' *Int. J. Mach. Learn. Cybern.*, vol. 9, no. 5, pp. 721–726, May 2018.

[101] Z. Gao, X. Wang, Y. Yang, Y. Li, K. Ma, and G. Chen, ''A channel-fused dense convolutional network for EEG-based emotion recognition,'' *IEEE Trans. Cognit. Develop. Syst.*, vol. 13, no. 4, pp. 945–954, Dec. 2020.

[102] X. Chai, Q. Wang, Y. Zhao, X. Liu, O. Bai, and Y. Li, ''Unsupervised domain adaptation techniques based on auto-encoder for non-stationary EEG-based emotion recognition,'' *Comput. Biol. Med.*, vol. 79, pp. 205–214, Dec. 2016.

[103] D. J. Hemanth, J. Anitha, and L. H. Son, ''Brain signal based human emotion analysis by circular back propagation and deep Kohonen neural networks,'' *Comput. Elect. Eng.*, vol. 68, pp. 170–180, May 2018.

[104] N. Kumar, K. Khaund, and S. M. Hazarika, ''Bispectral analysis of EEG for emotion recognition,'' *Proc. Comput. Sci.*, vol. 84, pp. 31–35, May 2016.

[105] Z. Mohammadi, J. Frounchi, and M. Amiri, ''Wavelet-based emotion recognition system using EEG signal,'' *Neural Comput. Appl.*, vol. 28, no. 8, pp. 1985–1990, Aug. 2017.

[106] A. Mert and A. Akan, ''Emotion recognition from EEG signals by using multivariate empirical mode decomposition,'' *Pattern Anal. Appl.*, vol. 21, no. 1, pp. 81–89, Feb. 2018.

[107] N. Thammasan, K. Moriyama, K.-I. Fukui, and M. Numao, ''Familiarity effects in EEG-based emotion recognition,'' *Brain Informat.*, vol. 4, no. 1, pp. 39–50, Mar. 2017.

[108] S. Ahmad, K. Li, H. A. I. Eddine, and M. I. Khan, ''A biologically inspired cognitive skills measurement approach,'' *Biologically Inspired Cogn. Archit.*, vol. 24, pp. 35–46, Apr. 2018.

[109] R. Ikramov, V. Ivanov, S. Masyagin, R. Shakirov, I. Sirazidtinov, G. Succi, A. Thapaliya, A. Tormasov, and O. Zufarova, ''Initial evaluation of the brain activity under different software development situations,'' in *Proc. Int. Conf. Softw. Eng. Knowl. Eng.*, Jul. 2019, pp. 741–777.

[110] S. Lee, D. Hooshyar, H. Ji, K. Nam, and H. Lim, ''Mining biometric data to predict programmer expertise and task difficulty,'' *Cluster Comput.*, vol. 21, no. 1, pp. 1097–1107, Mar. 2018.

[111] J. Medeiros, C. Teixeira, R. Couceiro, J. Castelhano, M. C. Branco, G. Duarte, C. Duarte, J. Duraes, H. Madeira, and P. Carvalho, ''Software code complexity assessment using EEG features,'' in *Proc. 41st Annu. Int. Conf. IEEE Eng. Med. Biol. Soc. (EMBC)*, Jul. 2019, pp. 1413–1416.

[112] E. Kim, D.-S. Kim, F. Ahmad, and H. Park, ''Pattern-based Granger causality mapping in fMRI,'' *Brain Connectivity*, vol. 3, no. 6, pp. 569–577, Dec. 2013.

[113] F. Shaffer and J. P. Ginsberg, ''An overview of heart rate variability metrics and norms,'' *Frontiers Public Health*, vol. 5, p. 258, Sep. 2017.

[114] N. H. Naqvi and A. Bechara, ''Skin conductance: A psychophysiological approach to the study of decision making,'' *Methods Mind*, pp. 103–122, Jun. 2006.

[115] B. Nakisa, M. N. Rastgoo, D. Tjondronegoro, and V. Chandran, ''Evolutionary computation algorithms for feature selection of EEG-based emotion recognition using mobile sensors,'' *Expert Syst. Appl.*, vol. 93, pp. 143–155, Mar. 2018.

[116] H. Kaya, F. Gürpinar, and A. A. Salah, ''Video-based emotion recognition in the wild using deep transfer learning and score fusion,'' *Image Vis. Comput.*, vol. 65, pp. 66–75, Sep. 2017.

[117] S. E. Kahou, X. Bouthillier, P. Lamblin, C. Gulcehre, V. Michalski, K. Konda, S. Jean, P. Froumenty, Y. Dauphin, N. Boulanger-Lewandowski, R. C. Ferrari, M. Mirza, D. Warde-Farley, A. Courville, P. Vincent, R. Memisevic, C. Pal, and Y. Bengio, ''EmoNets: Multimodal deep learning approaches for emotion recognition in video,'' *J. Multimodal User Interfaces*, vol. 10, no. 2, pp. 99–111, Jun. 2016.

[118] I. B. Mauss, M. D. Robinson, and emotion, ''Measures of emotion: A review,'' *Cognit. Emotion*, vol. 23, no. 2, pp. 209–237, 2009.

[119] G. Valenza, L. Citi, A. Lanatá, E. P. Scilingo, and R. Barbieri, ''Revealing real-time emotional responses: A personalized assessment based on heartbeat dynamics,'' *Sci. Rep.*, vol. 4, no. 1, pp. 1–13, May 2015.

[120] F. T. Sun, C. Kuo, H. T. Cheng, S. Buthpitiya, P. Collins, and M. Griss, ''Activity-aware mental stress detection using physiological sensors,'' in *Proc. Int. Conf. Mobile Comput., Appl.* Berlin, Germany: Springer, Oct. 2010, pp. 282–301.

[121] A. Liaw and M. Wiener, ''Classification and regression by randomforest,'' *R News*, vol. 2, no. 3, pp. 18–22, Dec. 2002.

[122] A. Criminisi, J. Shotton, and E. Konukoglu, ''Decision forests: A unified framework for classification, regression, density estimation, manifold learning and semi-supervised learning,'' *Found. Trends Comput. Graph. Vis.*, vol. 7, nos. 2–3, pp. 81–227, Feb. 2012.

[123] H. Cecotti and A. Gräser, ''Convolutional neural network with embedded Fourier transform for EEG classification,'' in *Proc. 19th Int. Conf. Pattern Recognit.*, Dec. 2008, pp. 1–4.

[124] M. Lopez, J. G. C. Arriaga, J. P. Nigenda Álvarez, R. T. González, J. A. Elizondo-Leal, J. E. Valdez-García, and B. Carrión, ''Virtual reality vs traditional education: Is there any advantage in human neuroanatomy teaching?'' *Comput. Electr. Eng.*, vol. 93, Jul. 2021, Art. no. 107282.

[125] S. Moharreri, N. J. Dabanloo, and K. Maghooli, "Modeling the 2D space of emotions based on the Poincare plot of heart rate variability signal," *Biocybernetics Biomed. Eng.*, vol. 38, no. 4, pp. 794–809, 2018.

[126] H. J. Kim and J. H. Yang, "Takeover requests in simulated partially autonomous vehicles considering human factors," *IEEE Trans. Human-Mach. Syst.*, vol. 47, no. 5, pp. 735–740, Oct. 2017.

[127] L. F. C. Figueredo, R. C. Aguiar, L. Chen, S. Chakrabarty, M. R. Dogar, and A. G. Cohn, "Human comfortability: Integrating ergonomics and muscular-informed metrics for manipulability analysis during human-robot collaboration," *IEEE Robot. Autom. Lett.*, vol. 6, no. 2, pp. 351–358, Apr. 2020.

[128] A. Hariharan and M. T. P. Adam, "Blended emotion detection for decision support," *IEEE Trans. Human-Mach. Syst.*, vol. 45, no. 4, pp. 510–517, Aug. 2015.

SUMAN KALYAN SARDAR received the Ph.D. degree from Hanyang University, South Korea. He is a Research Professor with the Department of Industrial and Systems Engineering, Gyeongsang National University. He is currently working in human factors and human–computer interaction to design, deploy, and evaluate technologies that revolve around human life.

NAVEEN KUMAR received the Ph.D. degree in HCI design from the Indian Institute of Technology, Delhi. He was a Postdoctoral Researcher with the Department of Industrial and Systems Engineering, Gyeongsang National University, South Korea. The aim of his research is to study the human factors in the context of smart factory. His research interests include human–computer interaction, user experience design, cognitive ergonomics, virtual reality, and design research methodologies.

SEUL CHAN LEE is an Assistant Professor with the Department of Industrial and Systems Engineering, Gyeongsang National University. His research interests include to make systems and devices better based on the theories and methodologies of human factors and human–computer interaction, especially in the fields of autonomous vehicle, VR/AR, and smart factory.